Supplemental Material
Neural Field Convolutions by Repeated Differentiation

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Table 1. Different convolution methods. n is the size of the filter, m the size of the signal (samples or weights to represent it), and d the signal dimension.

	Time	Spat. vary	Noisy	Cont.
Classic	$O(m \times n^d)$	✓	×	×
Fourier	$O(m \times \log(m) \times d)$	×	×	×
Monte Carlo	$O(m \times n)$	✓	✓	✓
SAT	$O(m \times d)$	✓	×	×
Mip-NeRF	$O(m)$	✓	×	✓
INSP	$O(m)$	×	×	✓
Ours	$O(m)$	✓	×	✓

Table 2. Architecture details of our integral fields.

Application	#Layers	#Features	#Trainable Params.
Images[1]	5	256	270,851
Images[2]	5	512	1,065,987
Videos	9	256	534,019
Geometry	5	256	270,851
Audio	5	256	270,851
Animation	5	256	270,851

[1] Low-resolution (256x256) images used for large-scale comparisons.
[2] High-resolution (3000x3000) images used for displaying results.

Table 3. Accuracy of kernels and time to optimize them.

m	3		7		13		24	
n	1	2	1	2	1	2	1	2
MSE	1.6e-1	1.5e-2	1.5e-2	7.9e-4	4.0e-3	7.6e-5	1.1e-3	2.3e-5
Time (s)	3	25	4	60	6	75	9	132

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1 CONVOLUTION METHODS

In Tab. 1 we compare different solutions to the convolution problem.

2 INTEGRAL FIELD MODEL DETAILS

In Tab. 2 we give details of network architectures for the repeated integral fields we use per application. In all cases we use a multi-layer perceptron (MLP). Similar to Lindell et al. [2021], we observed best results with Swish [Ramachandran et al. 2017] activation functions. We report the number of hidden layers, the number of features per layer, and the resulting number of trainable parameters.

3 KERNELS

In Tab. 3 we provide details on our optimized kernels. Here, we consider a 1D Gaussian kernel, represented by different numbers m of Diracs, using different orders of differentiation n. We give the reconstruction error in terms of the mean squared error (MSE) and the time (in seconds) our unoptimized implementation takes to obtain a converged result.

REFERENCES

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